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IoT-Based Image Segmentation and Fuzzy Mamdani for Ceramic Insulator Contaminant Identification

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ABSTRACT

Ceramic insulators on 150 kV transmission lines are prone to contamination from dust and moss, which can degrade insulation performance and increase the risk of system failure. This study aims to identify insulator contaminants using image processing techniques and Mamdani fuzzy logic integrated with an Internet of Things (IoT) platform to assess the dielectric strength of 150 kV ceramic insulators. The method involves capturing images of the insulator surface using a monocular digital microscope, applying OpenCV-based image processing for segmentation and quantification of contamination, and classifying contamination levels using Mamdani fuzzy logic. The results show that the system can accurately detect the percentage of dust and moss contamination. The processed image data are used as input to the fuzzy system to determine the dielectric strength of the insulator. Simulations demonstrate consistent classification of contamination into three levels: low, medium, and high. The system is integrated with the Ubidots IoT platform for real-time monitoring of insulator conditions. As contamination levels increase, the insulator's breakdown voltage decreases, with dust having a greater impact than moss, especially under high humidity conditions. The dielectric strength ranges from 45 kV to 110 kV, with values below 60 kV considered critical.

Keywords: Ceramic Insulator 1; Contaminants Dust Moss and IoT 2; OpenCV 3; Mamdani Fuzzy Logic 4; Dielectric Strength 5

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1. INTRODUCTION

The condition of the insulators on the 150 kV Koto Panjang - Payakumbuh transmission network is often affected by extreme environmental factors, especially high humidity[1]. Humid environmental conditions and the presence of contaminants from temperature and dust can affect the performance of the insulator. Data shows that the average humidity in this area reaches 80%, with contaminants such as dust, salt, and other chemicals that can accelerate the degradation of the insulator [2] .

In ideal conditions, dielectric strength is said to be good, namely being able to withstand voltage for a long period of time without experiencing insulation failure. The standard insulator voltage or BIL of the insulator is around 110 kV, this standard is used as a limit for the insulator to withstand without experiencing failure [2] .

International standards recommend that insulators must be able to operate with leakage currents below 5 μA in dry conditions. The main function of the insulator on overhead lines is to mechanically support the conductor and electrically isolate it from the tower, which is at ground potential [3]. In today's modern era, we can implement IoT-BASED isolator monitoring [7] . This contamination can cause a decrease in insulation value, increase the risk of *flashover* , and even electrical system failure. Therefore, it is important to monitor contamination levels regularly [8] .

With insulator monitoring still being carried out manually, there is a risk of delays in detecting changes in insulator conditions that can result in reduced dielectric resistance or other disturbances [9] . However, in the presence of contaminants, this value can increase significantly [10] . In an effort to increase efficiency and accuracy by using digital image processing and fuzzy logic-based methods, Mamdani is the right solution to identify the type of contaminant. This research has a crucial role in ensuring the reliability and safety of the electrical system. By knowing the impact of dust and moss contaminants on insulators, preventive measures can be taken to minimize the risk of disruption to the system. In addition, the use of IoT technology in insulator monitoring can increase operational efficiency and reduce maintenance costs in the long term.

1. 1 Theoretical Framework

In general, the use of transmission lines is based on the need to deliver power from generating stations to load centers over relatively long distances. This is because power plants, such as hydropower, coal-fired, or gas turbine plants, are usually located near primary energy sources, while load centers are situated in urban areas. To minimize these losses, transmission systems typically employ high or even extra-high voltages, since the higher the voltage used, the smaller the current that flows, thereby reducing power losses caused by conductor resistance. The transmission system operates with energy losses that occur due to voltage drops [12].

In the electric power industry, outdoor insulators are widely used to maintain electrical insulation from distribution to transmission lines and to support the mechanical load between conductors and the ground in power system equipment. Most of the time, insulators are exposed to continuous moisture and both soluble and insoluble contamination (such as dust and sand, chemical products, and salts) caused by natural or anthropogenic factors [12]. An insulator essentially has a limit to the conductivity resistance of its specific resistivity. For insulators installed outdoors, their resistance decreases due to the influence of air pollution such as dust, smoke, and sea salt, as well as wet and dry cycles that adhere to the insulator surface and form a contaminant layer.

This condition leads to the formation of dry bands on the insulator surface, which, under high voltage stress, can result in leakage currents and arc discharges on the insulator surface [13]. In a study conducted by [14], it is explained that insulators function to maintain the reliability of power transmission by separating energized and non-energized parts. The study also highlights that insulators may experience disturbances due to environmental factors such as temperature, humidity, and pollutants, which can lead to phenomena such as arcing discharge. This indicates the importance of maintaining and monitoring the condition of insulators to prevent system failures [14]. The system used for large-scale transmission of electrical energy from the generating source to the load center is referred to as a transmission line. According to [15]an automatic inspection system was developed to detect and locate insulators on power transmission lines using unmanned aerial vehicles (UAVs) equipped with stereoscopic vision technology.

This research aims to address the limitations of manual inspection, which is often inefficient and constrained by environmental conditions. The proposed system consists of a UAV module, an embedded industrial computer, a binocular visual perception module, and a control module. Meanwhile, Pernebayeva et al. (2017) developed a technique for evaluating the surface condition of high-voltage insulators by utilizing digital image processing. The study employed Gabor filters and standard deviation filters for feature extraction from images of ceramic insulators under snow, ice, and water conditions [16]. According to [17], this study discusses a monitoring system for high-voltage transmission lines based on the Internet of Things (IoT). The authors, Aseel Yousif Mohammed and Rabee Moafaq Hagem, highlight various challenges faced by transmission lines due to environmental factors such as extreme weather and intentional damage.

Ceramic insulators are one of the most widely used types of insulators in power systems, particularly in transmission and distribution lines. The ceramic material used has properties that make it resistant to high temperatures, corrosion, and extreme environmental conditions, making it highly suitable for outdoor applications. In addition, ceramic insulators possess good mechanical strength, allowing them to withstand conductor tensile loads as well as wind pressure. From an electrical perspective, these insulators have high insulation resistance that remains relatively stable even when exposed to weather changes. However, ceramic insulators also have weaknesses, such as being easily broken or cracked due to mechanical impact, and being prone to the accumulation of contaminants like dust, salt, and moss on their surfaces. Made from ceramic material, these insulators exhibit strong resistance to high temperatures and corrosion, and are frequently used in outdoor applications[12].

2. RESEARCH METHOD

This study uses 150 kV ceramic insulators with contamination in the form of dust and moss as the main objects. The equipment used includes a monocular digital microscope for capturing images of the insulator surface, a laptop/PC with Python software (OpenCV) for image processing, MATLAB (Fuzzy Logic Toolbox) for Mamdani fuzzy analysis, connected to the Ubidots platform as an online data visualization medium.

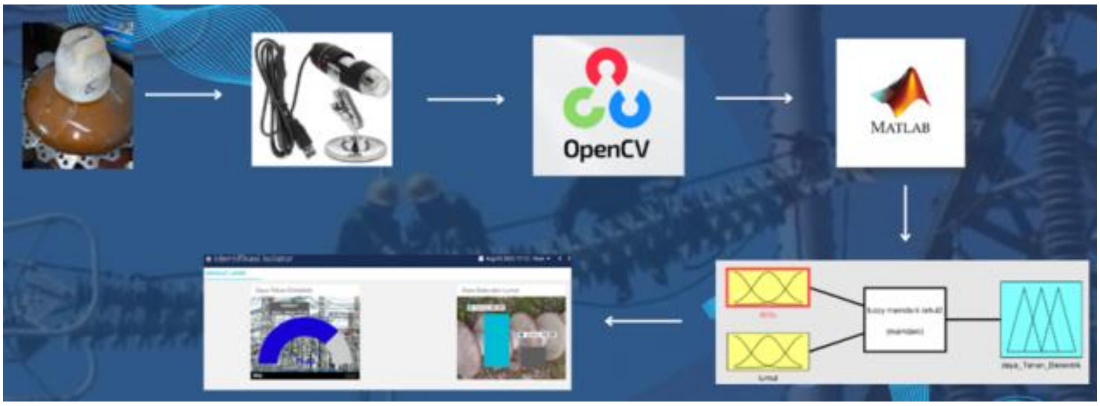

Figure 1Research Overview

The equipment used includes a monocular digital microscope for capturing images of the insulator surface, a laptop/PC with Python software (OpenCV) for image processing, MATLAB (Fuzzy Logic Toolbox) for Mamdani fuzzy analysis, and the Mamdani fuzzy results are connected to the Ubidots platform as a data visualization medium. The research phase began with image acquisition of the isolator using a monocular digital microscope. The isolator was divided into several sub-sections to allow for more detailed and even contamination detection. The resulting images were then processed using OpenCV to segment the contaminants. Dust contamination was analyzed using the *K-Means Clustering method* . The K-Means Clustering method is an image segmentation algorithm that works by dividing a collection of pixels into a number of groups (*clusters*) based on similarity in feature values, such as intensity or color components.

$$J = \sum_{k=1}^{k} \sum_{xi \in ck} ||xi - \mu k||^{2} \quad (1)$$

In equation (1) of the K-Means objective function, there are several important parameters that have special meaning. J represents the cost function value or total error in the clustering process. This value indicates how far the data is distributed from the specified cluster center. The smaller the value, the better the segmentation quality because the pixels within the cluster are more homogeneous. Next, is the number of clusters determined at the beginning of the process. The value of K functions as the number of color or intensity groups that will be formed in the image. The choice of K significantly affects the segmentation results, as too small a number of clusters can result in loss of image detail, while too large a number can result in oversegmentation. x indicates the i-th data or pixel in the image. Each pixel is treated as a data point with a specific feature value, such as grayscale intensity or color combination (R, G, B). These pixels will be grouped based on their similarity in distance to the centroid. Then, k represents the set of pixels included in the kth cluster. In other words, each cluster contains a set of pixels that have similar characteristics, for example, bright colors are grouped as dust or dull green colors are grouped as moss. Finally, k is the centroid of the kth cluster.

The centroid is the center point calculated based on the average value of all pixels in the cluster. The position of the centroid will continue to be updated at each iteration until it reaches a stable condition. In image segmentation, this centroid serves as a representation of the dominant color or intensity of a cluster. The stages of the K-Means algorithm for image segmentation can be explained.

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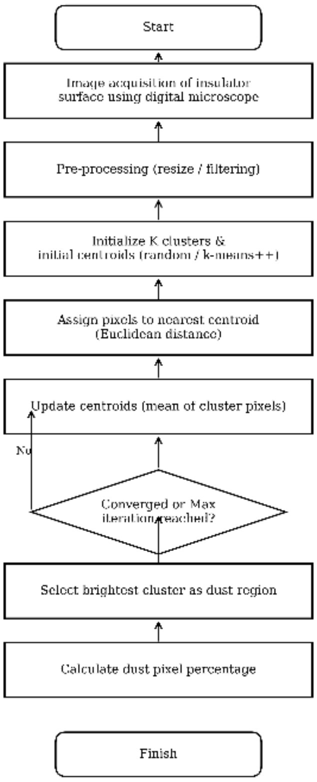

Figure 2. Flowchart

$$D_{px} = \sum_{i=1}^{N} \delta(\text{pixsel}_{i} \in \text{dust}) \quad (2)$$

In equation (2) is to find the dust pixels. The number of dust pixels is denoted by D_{px} . This value represents the total number of pixels classified as dust in the segmented image. Meanwhile, N is the total number of pixels in the image. For example, if the resized image measures 400 × 600 pixels, the total is 240,000 pixels. Each pixel in the image is represented as $_{i}$ pixel . i.e. the i -th pixel of the entire image data. To determine whether a pixel is included in the dust category or not, the indicator function or Kronecker delta is used. This function gives a value of 1 if the pixel is detected as dust (mask value 255), and a value of 0 if the pixel is not dust (mask value 0). Thus, the number of dust pixels (D_{px}) is obtained from the sum of all indicator functions in the image, so that only pixels that are truly included in the dust category are counted. Next, the percentage value of dust pixels is denoted by (D_{px}). This value is obtained by comparing the number of dust pixels (D_{px}) to the total number of pixels in the image (N), then multiplying by 100%. This calculation produces a value in the form of a percentage, which shows how much of the insulator surface is covered by dust compared to the total image area. [11] . While moss is detected through *HSV-based thresholding* . Basic Concept of Thresholding Thresholding is a simple image segmentation method that aims to separate objects from the background based on intensity or color values. The main principle is to provide a certain threshold, so that pixels with values above the threshold are set as objects (foreground), while pixels below the threshold are considered background. HSV (Hue, Saturation, Value) in Image Processing The HSV color system is closer to the way humans see color than the RGB model. HSV consists of: Hue (H) represents the type of color (red, green, blue, etc.) with a range of 0–180 in OpenCV. Saturation (S) the level of color saturation, range 0–255. Value (V) brightness or light intensity, range 0–255.

$$L_{pz} = \sum_{i=1}^{N} \delta(\text{pixsel}_{i} \in \text{moss}) \quad (3)$$

In the image segmentation process, the number of moss pixels is denoted by L_{pz} which shows the total pixels classified as moss. Meanwhile, N represents the total number of pixels in the image after the resizing process , for example at a size of 400 × 600 resulting in 240,000 pixels. Each pixel in the image is denoted as pixel_i , which is the value of the i-th pixel. To determine whether a pixel belongs to the moss category or not, the indicator function $\delta(\cdot)$ or Kronecker delta is used. This function has a value of **1** if the i-th pixel is detected as moss (mask value 255), and a value of **0** if the pixel is not moss (mask value 0). Thus, the calculation of the number of moss pixels is done by adding up the results of the indicator function of all pixels in the image. By utilizing HSV, the segmentation process becomes more flexible because color separation can be done specifically without being significantly affected by light intensity, in contrast to the RGB color space which is very sensitive to changes in lighting. HSV-Based Thresholding Process The stages of this method are Color Conversion RGB/BGR images are converted to HSV color space. Color Range Determination determines the lower bound and upper bound on the H, S, and V channels. For example, moss is usually in the dull green range ($H \approx 35–90$). Masking performs an inRange operation to produce a binary image (mask). Pixels within the HSV range will be assigned a white value (255), while those outside the range will be assigned a black value (0). Post-Processing: use morphological operations (erosion, dilation, opening, closing) or smoothing to reduce noise and clarify the object area. The advantages are simple, fast computation, effective for objects with certain dominant colors [12] .

The segmentation results in the form of the number of dust and moss pixels are calculated as a percentage of the total image area. The contamination percentage is then used as input to the Mamdani fuzzy logic system. The fuzzy process includes fuzzification to convert input data into membership degrees, determining IF–THEN rules that link the contamination level to dielectric resistance, inference using the min–max method, and defuzzification using the centroid method to produce an output value in the form of an estimated dielectric voltage (kV). The final stage of the research is integration with the IoT system. Mamdani's fuzzy results are connected to the Ubidots platform for data visualization. This allows insulator conditions to be monitored in real time via an interactive dashboard featuring graphs and gauge indicators.

3. RESULTS AND DISCUSSION

This research begins with a preparation stage that includes a literature study related to 150 kV ceramic insulators, the effects of dust and moss contaminants, digital image processing methods, Mamdani fuzzy logic, and the application of the Internet of Things (IoT). The research location is at the High Voltage Systems Laboratory of the Padang Institute of Technology with research equipment in the form of 150 kV ceramic insulators, a monocular digital microscope, a laptop/PC with Python (OpenCV) and MATLAB software, and the Ubidots IoT platform.

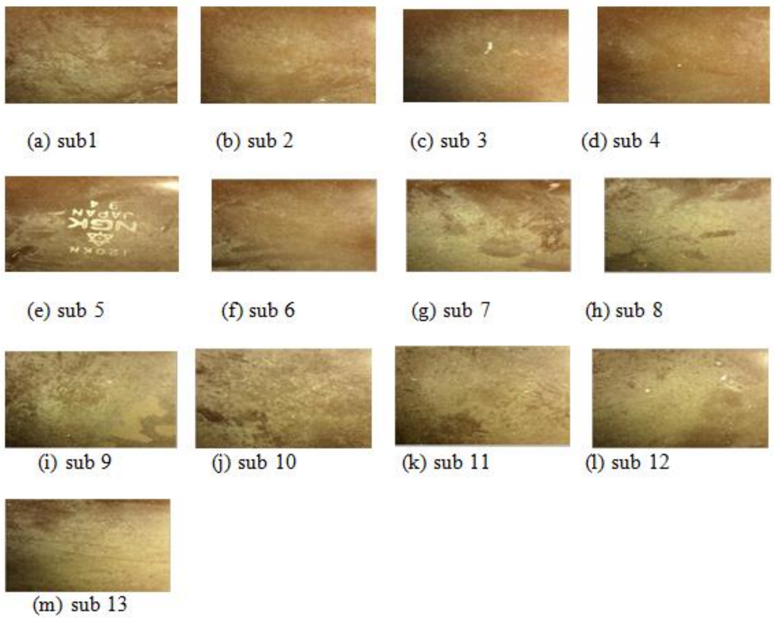

Figure 3. Capture Results of the Surface Image of Insulator 1

This study used five isolator samples. Each sample was documented by photographing the isolator surface using a monocular digital microscope, then divided into several sub-sections to obtain a more even variation in contamination conditions. The collected image data was analyzed using OpenCV to segment contaminants. Moss segmentation was performed by converting the image from BGR to HSV, then assigning a dull green color range as the moss area. Meanwhile, dust segmentation was performed using the K-Means Clustering method (K=3), with the lightest colored cluster selected as dust. The segmentation results produce the number of moss, dust, and clean area pixels which are then converted into percentages.

The calculation results are used as input to the Mamdani Fuzzy logic system. The fuzzy process includes a fuzzification stage to convert the dust and moss contamination values into membership degrees, determining a rule base based on IF–THEN rules that connect the contamination level with dielectric resistance, inference using the Mamdani min–max method, and defuzzification using the centroid method to produce output in the form of dielectric voltage estimates in kV units. In the final stage, the system results are integrated with the Ubidots IoT platform. Data on the percentage of dust and moss contamination along with the dielectric resistance value of the insulator are displayed through an interactive dashboard in the form of graphs and gauge indicators, so that the condition of the insulator can be monitored in real-time.

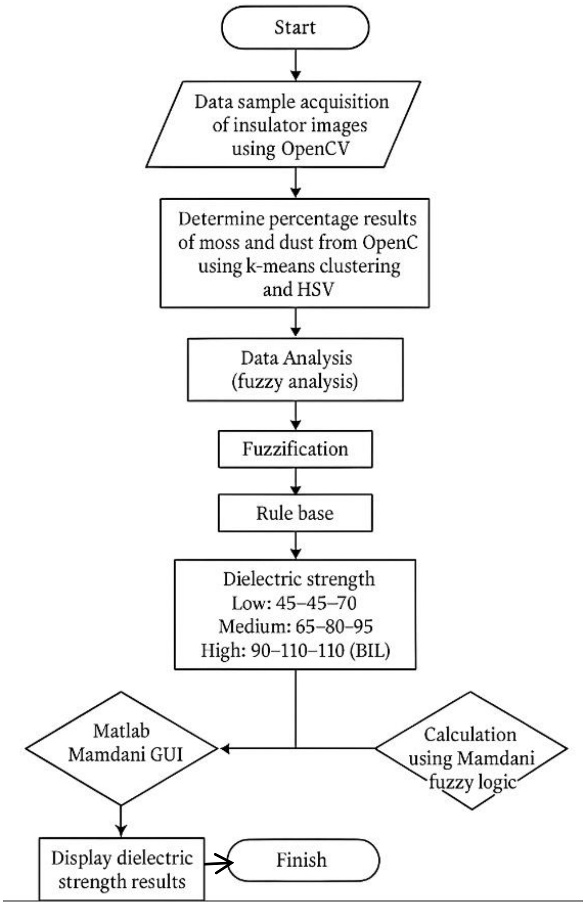

Figure 4. Flowchart

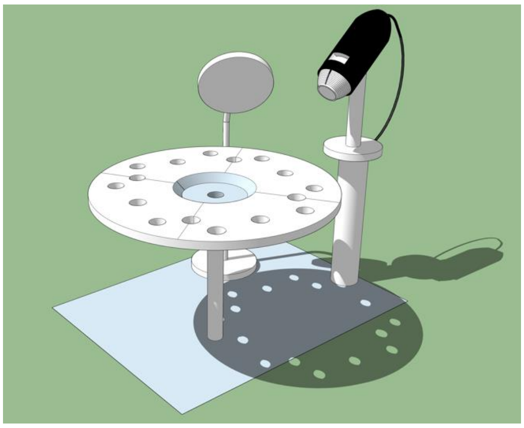

Figure 5. System design

3.1. Data Management to Determine the Percentage of Dust and Moss Contaminants

To calculate the percentage of dust contaminants in image (2) sub 1, dust pixels are identified using the K-Means Clustering method. The first stage is to reshape the image into a pixel array with size (H, W, 3), where H indicates height, W width, and the number 3 represents the BGR color channel. This reshaping process only changes the shape of the array without changing the values in it. The data is then converted (cast) to float32 format because the cv2.kmeans function requires that data type . The algorithm termination criteria are determined by the condition of a maximum of 100 iterations or a change in value (epsilon) < 1.0. If one of them is met, the process is stopped. The k value is set to 3, meaning the pixels are grouped into three color clusters. The process is run 10 times (attempts=10) with different initializations, then the best result is selected based on the smallest cost function. The initial centroid is chosen randomly. The output is a label indicating which cluster each pixel belongs to (0…K–1) and the BGR color centroid coordinates in float format. Next, the brightness level of each centroid is calculated using a pseudo-grayscale formula using the vector [1, 0.587, 0.114] × [B, G, R], which emphasizes the blue channel [13] . With this method, pixels are grouped into three main clusters: light (dust), brown (insulator surface), and other colors (not dust). The final result is a binary image with values 0 (black, not dust) and 255 (white, dust). The white area represents the dust pixels in the segmentation results. The percentage of dust is calculated by dividing the number of dust pixels by the total number of pixels in the sub-image, then multiplying by 100%. The total number of pixels can be obtained from the details of the full insulator image.

Meanwhile, the percentage of moss contaminants was calculated using the HSV-based Thresholding method. The moss color range was determined from the experimental results, namely HSV Lower = (20, 20, 20) and HSV Upper = (90, 255, 255). In the first stage, the BGR image was converted to HSV to facilitate color separation. The HSV model consists of Hue (H) for the color type, Saturation (S) for the saturation level, and Value (V) for brightness. The masking process produces a binary image where pixels with HSV values within the range are considered moss (1/white), while those outside the range are considered non-moss (0/black). To reduce noise, morphological operations were used with a 5×5 matrix. After segmentation was complete, the number of moss pixels was calculated and converted into a percentage, namely the number of moss pixels divided by the total image pixels, then multiplied by 100%. This process was carried out consistently on sub-1 to sub-13 to obtain the percentage of dust and moss contaminants in all insulator samples.

3.2. Surface Image Results of Five Insulator Samples

Table 1. Results of Dust and Moss Image Segmentation on Five Isolator Samples

Insulator	Dust contaminant variable (%)	Moss contaminant variable (%)
1	16.8	4.5
2	46.2	2.8
3	12.60	70.39
4	13.11	24.95
5	28.92	21.21

Table 1 presents the percentage of dust and moss contamination in five insulator samples. In the first insulator, dust contamination was recorded at 16.8 % and moss at 4.5%, indicating a relatively clean condition with a predominance of light dust. The second insulator showed higher dust contamination, namely 46.2 % with moss at 2.8%, so it can be concluded that dust is the dominant factor. In contrast, the third insulator had low dust contamination of 12.60% but very high moss at 70.39%, indicating moss as the dominant contaminant that has the potential to greatly reduce dielectric resistance. In the fourth insulator, the percentage of dust was 13.11 % and moss at 24.95%, indicating a significant influence of moss although not as high as the third insulator. Meanwhile, the fifth insulator showed dust contamination of 28.92 % and moss at 21.21%, indicating that both contaminants were present at moderate intensity. Overall, these results indicate a variation in contamination patterns, with some insulators being more affected by dust, while others are more predominantly contaminated by moss, thus both can affect dielectric performance differently.

3.2.1 Matlab results using the Mamdani Fuzzy Method with input variables of dust and mosscontaminants in Isolator Sample 1

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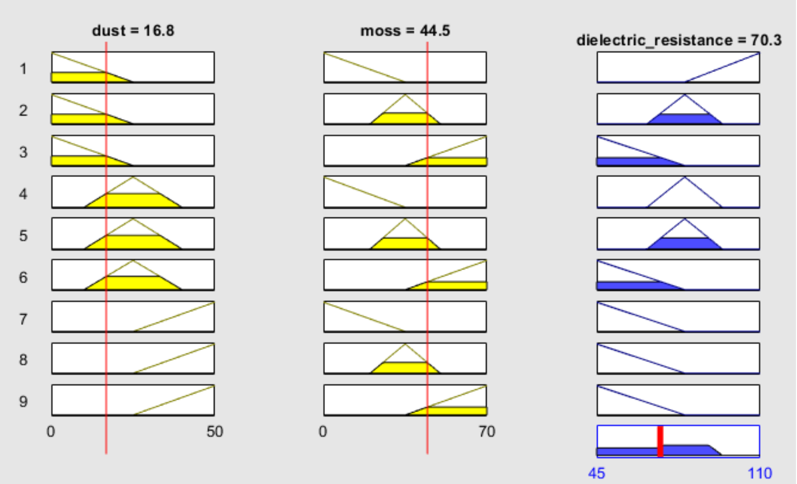

Figure 6. Results of Fuzzy Mamdani Isolator 1

Figure 4 shows the results of data processing using the Mamdani Fuzzy System with inputs in the form of dust percentages of 16.8% and moss of 44.5%. The fuzzy membership graph for the dust variable is displayed on the left side, while the membership graph for the moss variable is displayed in the middle. The red vertical line on each graph indicates the position of the input value entered into the system. Meanwhile, the graph on the right side represents the output variable in the form of dielectric resistance. Based on the inference results, the system produces a dielectric resistance value of 71.4 kV. This value is obtained through a series of fuzzification processes, rule application (rule base), and defuzzification using the centroid method.

3.2.2 The Effect of Dust and Moss Contaminants on Dielectric Resistance

Table 2. Mamadani Fuzzy Results of Dust and Moss Variables for Five Isolators

Insulator	Dust contaminant variable (%)	Moss contaminant variable (%)	Dielectric Resistance (Matlab kv)
1	16.8	4.5	75.4
2	46.2	2.8	56.7
3	12.60	70.39	58.5
4	13.11	24.95	91.6
5	28.92	21.21	74.9

Based on the data in Table 2, it can be seen that the dielectric resistance value is greatly influenced by the percentage of dust and moss contamination. In the first insulator with 16.8% dust contamination and 4.5% moss, the result was 75.4 kV, which indicates that moderate dust content with low moss is still able to maintain a fairly high dielectric voltage. The second insulator has the highest dust contamination of 46.2 % with 2.8% moss, so the voltage value drops significantly to 56.7 kV. This confirms that high amounts of dust play a dominant role in reducing the insulator resistance. Conversely, in the third insulator, although the dust is relatively low (12.60 %), the high moss contamination (70.39%) reduces the dielectric voltage to 58.5 kV. This proves that moss also has a negative impact, although its influence is not as dominant as dust. The fourth insulator, with 13.11% dust and 24.95% moss, actually produced the highest value of 91.6 kV, indicating that the combination of low dust and moderate moss still supports the insulator's strength. Meanwhile, the fifth insulator with 28.92% dust contamination and 21.21% moss produced a value of 74.9 kV, which is at an intermediate level.

4. CONCLUSION

Segmentation method performance The K-Means Clustering method was successfully used for dust segmentation, while the HSV-based Thresholding method was effective in detecting moss areas. Both methods were able to extract the percentage value of contaminants accurately from the insulator surface image. The results of the designed Mamdani fuzzy showed consistent results. Proven by matlab programming with input of dust and moss contaminant percentages and output of dielectric resistance. dust and moss contaminants on dielectric resistance, it can be concluded that both types of contaminants equally reduce the insulator's ability to withstand voltage. The effect of dust and moss contaminants on dielectric resistance is that in this study dust has the most significant effect with a sharp decrease due to the formation of a conductive layer on the insulator surface, while moss has a more gradual effect but still contributes to the degradation of dielectric resistance. Integration to Ubidots The developed system was successfully integrated with the Ubidots IoT platform, so that the calculation results (dust, moss input, and fuzzy output in the form of dielectric resistance) can be monitored in real-time through a cloud-based dashboard.

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

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BIOGRAPHIES OF AUTHORS

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